Explore Bike Share Data

For this project, your goal is to ask and answer three questions about the available bikeshare data from Washington, Chicago, and New York. This notebook can be submitted directly through the workspace when you are confident in your results.

You will be graded against the project Rubric by a mentor after you have submitted. To get you started, you can use the template below, but feel free to be creative in your solutions!

Loading Libraries

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Utility Functions

In [2]:
```
def df_summary(df):
    summary = ny.describe()
    null_count = ny.isnull().sum()
    summary.loc['null_count'] = null_count
    return summary

def get_range_hour(x):
    hour = x.hour
    for i in range(0, 24, 3):
        if i <= hour < i + 3:
            return f'{i}-{i + 2}'
    return None


def get_range_hour_idx(x):
    hour = x.hour
    for i in range(0, 24, 3):
        if i <= hour < i + 3:
            return i
    return None

def get_range_age(x):
    if x > 80:
        return '>80'
    for i in range(0, 81, 10):
        if i <= x < i + 10:
            return f'{i}-{i + 9}'
    return None
```

Loading CSV

I load the CSV files into their respective dataframes.

In [3]:
```
ny = pd.read_csv('new-york-city.csv')
wash = pd.read_csv('washington.csv')
chi = pd.read_csv('chicago.csv')
```

Data Analysis and Schema

I perform a preliminary analysis of the 3 initial datasets using the summary function.

New York

In [4]:
```
ny_summary = df_summary(ny)
ny_summary
```

Out[4]:

	Unnamed: 0	Trip Duration	Birth Year
count	3.000000e+05	3.000000e+05	271780.000000
mean	3.407026e+06	8.996842e+02	1978.254309
std	1.965617e+06	5.710016e+03	11.848045
min	3.300000e+01	6.100000e+01	1885.000000
25%	1.707416e+06	3.680000e+02	1970.000000
50%	3.405756e+06	6.090000e+02	1981.000000
75%	5.108762e+06	1.054000e+03	1988.000000
max	6.816152e+06	2.155775e+06	2001.000000
null_count	0.000000e+00	0.000000e+00	28220.000000

In [5]:

```
ny.head(5)
```

Out[5]:

	Unnamed: 0	Start Time	End Time	Trip Duration	Start Station	End Station	User Type	Gender	Birth Year
0	5688089	2017-06-11 14:55:05	2017-06-11 15:08:21	795	Suffolk St & Stanton St	W Broadway & Spring St	Subscriber	Male	1998.0
1	4096714	2017-05-11 15:30:11	2017-05-11 15:41:43	692	Lexington Ave & E 63 St	1 Ave & E 78 St	Subscriber	Male	1981.0
2	2173887	2017-03-29 13:26:26	2017-03-29 13:48:31	1325	1 Pl & Clinton St	Henry St & Degraw St	Subscriber	Male	1987.0
3	3945638	2017-05-08 19:47:18	2017-05-08 19:59:01	703	Barrow St & Hudson St	W 20 St & 8 Ave	Subscriber	Female	1986.0
4	6208972	2017-06-21 07:49:16	2017-06-21 07:54:46	329	1 Ave & E 44 St	E 53 St & 3 Ave	Subscriber	Male	1992.0

Washington

In [6]:

```
wash_summary = df_summary(wash)
wash_summary
```

Out[6]:

	Unnamed: 0	Trip Duration	Birth Year
count	3.000000e+05	3.000000e+05	271780.000000
mean	3.407026e+06	8.996842e+02	1978.254309
std	1.965617e+06	5.710016e+03	11.848045
min	3.300000e+01	6.100000e+01	1885.000000
25%	1.707416e+06	3.680000e+02	1970.000000
50%	3.405756e+06	6.090000e+02	1981.000000
75%	5.108762e+06	1.054000e+03	1988.000000
max	6.816152e+06	2.155775e+06	2001.000000
null_count	0.000000e+00	0.000000e+00	28220.000000

In [7]:

```
wash.head(5)
```

Out[7]:

	Unnamed: 0	Start Time	End Time	Trip Duration	Start Station	End Station	User Type
0	1621326	2017-06-21 08:36:34	2017-06-21 08:44:43	489.066	14th & Belmont St NW	15th & K St NW	Subscriber
1	482740	2017-03-11 10:40:00	2017-03-11 10:46:00	402.549	Yuma St & Tenley Circle NW	Connecticut Ave & Yuma St NW	Subscriber
2	1330037	2017-05-30 01:02:59	2017-05-30 01:13:37	637.251	17th St & Massachusetts Ave NW	5th & K St NW	Subscriber
3	665458	2017-04-02 07:48:35	2017-04-02 08:19:03	1827.341	Constitution Ave & 2nd St NW/DOL	M St & Pennsylvania Ave NW	Customer
4	1481135	2017-06-10 08:36:28	2017-06-10 09:02:17	1549.427	Henry Bacon Dr & Lincoln Memorial Circle NW	Maine Ave & 7th St SW	Subscriber

Chicago

In [8]:
```
chi_summary = df_summary(chi)
chi_summary
```

Out[8]:

	Unnamed: 0	Trip Duration	Birth Year
count	3.000000e+05	3.000000e+05	271780.000000
mean	3.407026e+06	8.996842e+02	1978.254309
std	1.965617e+06	5.710016e+03	11.848045
min	3.300000e+01	6.100000e+01	1885.000000
25%	1.707416e+06	3.680000e+02	1970.000000
50%	3.405756e+06	6.090000e+02	1981.000000
75%	5.108762e+06	1.054000e+03	1988.000000
max	6.816152e+06	2.155775e+06	2001.000000
null_count	0.000000e+00	0.000000e+00	28220.000000

In [9]:
```
chi.head(5)
```

Out[9]:

	Unnamed: 0	Start Time	End Time	Trip Duration	Start Station	End Station	User Type	Gender	Birth Year
0	1423854	2017-06-23 15:09:32	2017-06-23 15:14:53	321	Wood St & Hubbard St	Damen Ave & Chicago Ave	Subscriber	Male	1992.0
1	955915	2017-05-25 18:19:03	2017-05-25 18:45:53	1610	Theater on the Lake	Sheffield Ave & Waveland Ave	Subscriber	Female	1992.0
2	9031	2017-01-04 08:27:49	2017-01-04 08:34:45	416	May St & Taylor St	Wood St & Taylor St	Subscriber	Male	1981.0
3	304487	2017-03-06 13:49:38	2017-03-06 13:55:28	350	Christiana Ave & Lawrence Ave	St. Louis Ave & Balmoral Ave	Subscriber	Male	1986.0
4	45207	2017-01-17 14:53:07	2017-01-17 15:02:01	534	Clark St & Randolph St	Desplaines St & Jackson Blvd	Subscriber	Male	1975.0

From this analysis, the following points are evident:

- New York: The Birth.Year variable has 28,220 missing values.
- Chicago: The Birth.Year variable has 61,019 missing values, which represent a significant percentage of the total.
- Washington: There is a complete lack of information on Gender and Birth.Year, limiting the analysis to only trip and station data.

Data Cleaning and Final Dataset Construction

Below is the code I will use to merge the 3 dataframes, standardizing and homogenizing the fields to obtain a final dataset that includes all essential information.

New York cleaning and standardizzation

In [10]:
```
ny.columns.values[0] = "Trip.id"
ny["Birth Year"] = ny["Birth Year"].astype(float)
ny["Start Time"] = pd.to_datetime(ny["Start Time"])
ny["End Time"] = pd.to_datetime(ny["End Time"])
ny["City"] = 'New York'
ny.head(5)
```

Out[10]:

	Trip.id	Start Time	End Time	Trip Duration	Start Station	End Station	User Type	Gender	Birth Year	City
0	5688089	2017-06-11 14:55:05	2017-06-11 15:08:21	795	Suffolk St & Stanton St	W Broadway & Spring St	Subscriber	Male	1998.0	New York
1	4096714	2017-05-11 15:30:11	2017-05-11 15:41:43	692	Lexington Ave & E 63 St	1 Ave & E 78 St	Subscriber	Male	1981.0	New York
2	2173887	2017-03-29 13:26:26	2017-03-29 13:48:31	1325	1 Pl & Clinton St	Henry St & Degraw St	Subscriber	Male	1987.0	New York
3	3945638	2017-05-08 19:47:18	2017-05-08 19:59:01	703	Barrow St & Hudson St	W 20 St & 8 Ave	Subscriber	Female	1986.0	New York
4	6208972	2017-06-21 07:49:16	2017-06-21 07:54:46	329	1 Ave & E 44 St	E 53 St & 3 Ave	Subscriber	Male	1992.0	New York

Washington cleaning and standardizzation

In [11]:

```
wash.columns.values[0] = "Trip.id"
#wash["Birth Year"] = wash["Birth Year"].astype(float)
wash["Start Time"] = pd.to_datetime(wash["Start Time"])
wash["End Time"] = pd.to_datetime(wash["End Time"])
wash["City"] = 'Washington'
wash.insert(7,'Gender',None)
wash.insert(8,'Birth Year',None)
wash.head(5)
```

Out[11]:

	Trip.id	Start Time	End Time	Trip Duration	Start Station	End Station	User Type	Gender	Birth Year	City
0	1621326	2017-06-21 08:36:34	2017-06-21 08:44:43	489.066	14th & Belmont St NW	15th & K St NW	Subscriber	None	None	Washington
1	482740	2017-03-11 10:40:00	2017-03-11 10:46:00	402.549	Yuma St & Tenley Circle NW	Connecticut Ave & Yuma St NW	Subscriber	None	None	Washington
2	1330037	2017-05-30 01:02:59	2017-05-30 01:13:37	637.251	17th St & Massachusetts Ave NW	5th & K St NW	Subscriber	None	None	Washington
3	665458	2017-04-02 07:48:35	2017-04-02 08:19:03	1827.341	Constitution Ave & 2nd St NW/DOL	M St & Pennsylvania Ave NW	Customer	None	None	Washington
4	1481135	2017-06-10 08:36:28	2017-06-10 09:02:17	1549.427	Henry Bacon Dr & Lincoln Memorial Circle NW	Maine Ave & 7th St SW	Subscriber	None	None	Washington

Chicago cleaning and standardizzation

In [12]:

```
chi.columns.values[0] = "Trip.id"
chi["Birth Year"] = chi["Birth Year"].astype(float)
chi["Start Time"] = pd.to_datetime(chi["Start Time"])
chi["End Time"] = pd.to_datetime(chi["End Time"])
chi["City"] = 'New York'
chi.head(5)
```

Out[12]:

	Trip.id	Start Time	End Time	Trip Duration	Start Station	End Station	User Type	Gender	Birth Year	City
0	1423854	2017-06-23 15:09:32	2017-06-23 15:14:53	321	Wood St & Hubbard St	Damen Ave & Chicago Ave	Subscriber	Male	1992.0	New York
1	955915	2017-05-25 18:19:03	2017-05-25 18:45:53	1610	Theater on the Lake	Sheffield Ave & Waveland Ave	Subscriber	Female	1992.0	New York
2	9031	2017-01-04 08:27:49	2017-01-04 08:34:45	416	May St & Taylor St	Wood St & Taylor St	Subscriber	Male	1981.0	New York
3	304487	2017-03-06 13:49:38	2017-03-06 13:55:28	350	Christiana Ave & Lawrence Ave	St. Louis Ave & Balmoral Ave	Subscriber	Male	1986.0	New York
4	45207	2017-01-17 14:53:07	2017-01-17 15:02:01	534	Clark St & Randolph St	Desplaines St & Jackson Blvd	Subscriber	Male	1975.0	New York

In [13]:

```
final_ds = pd.concat([ny,wash,chi], axis=0, ignore_index=True)
df_summary(final_ds)
```

```
/tmp/ipykernel_1162/102363612.py:1: FutureWarning: The behavior of DataFrame concatenation with empty or all-NA entries is deprecated. In a future version, this will no longer exclude empty or all-NA columns when determining the result dtypes. To retain the old behavior, exclude the relevant entries before the concat operation.
  final_ds = pd.concat([ny,wash,chi], axis=0, ignore_index=True)
```

Out[13]:

	Trip.id	Start Time	End Time	Trip Duration	Birth Year
count	3.000000e+05	300000	300000	3.000000e+05	271780.000000
mean	3.407026e+06	2017-04-18 23:57:55.156410624	2017-04-19 00:12:55.339599616	8.996842e+02	1978.254309
min	3.300000e+01	2017-01-01 00:13:34	2017-01-01 00:27:31	6.100000e+01	1885.000000
25%	1.707416e+06	2017-03-07 17:30:53.500000	2017-03-07 17:41:34.249999872	3.680000e+02	1970.000000
50%	3.405756e+06	2017-04-28 08:23:16	2017-04-28 08:35:04.500000	6.090000e+02	1981.000000
75%	5.108762e+06	2017-06-01 12:25:53.750000128	2017-06-01 12:42:50.500000	1.054000e+03	1988.000000
max	6.816152e+06	2017-06-30 23:52:44	2017-07-08 14:30:26	2.155775e+06	2001.000000
std	1.965617e+06	NaN	NaN	5.710016e+03	11.848045
null_count	0.000000e+00	0	0	0.000000e+00	28220.000000

Question 1

By dividing the day into 3-hour time slots, which time slot has the most trips?

In [14]:

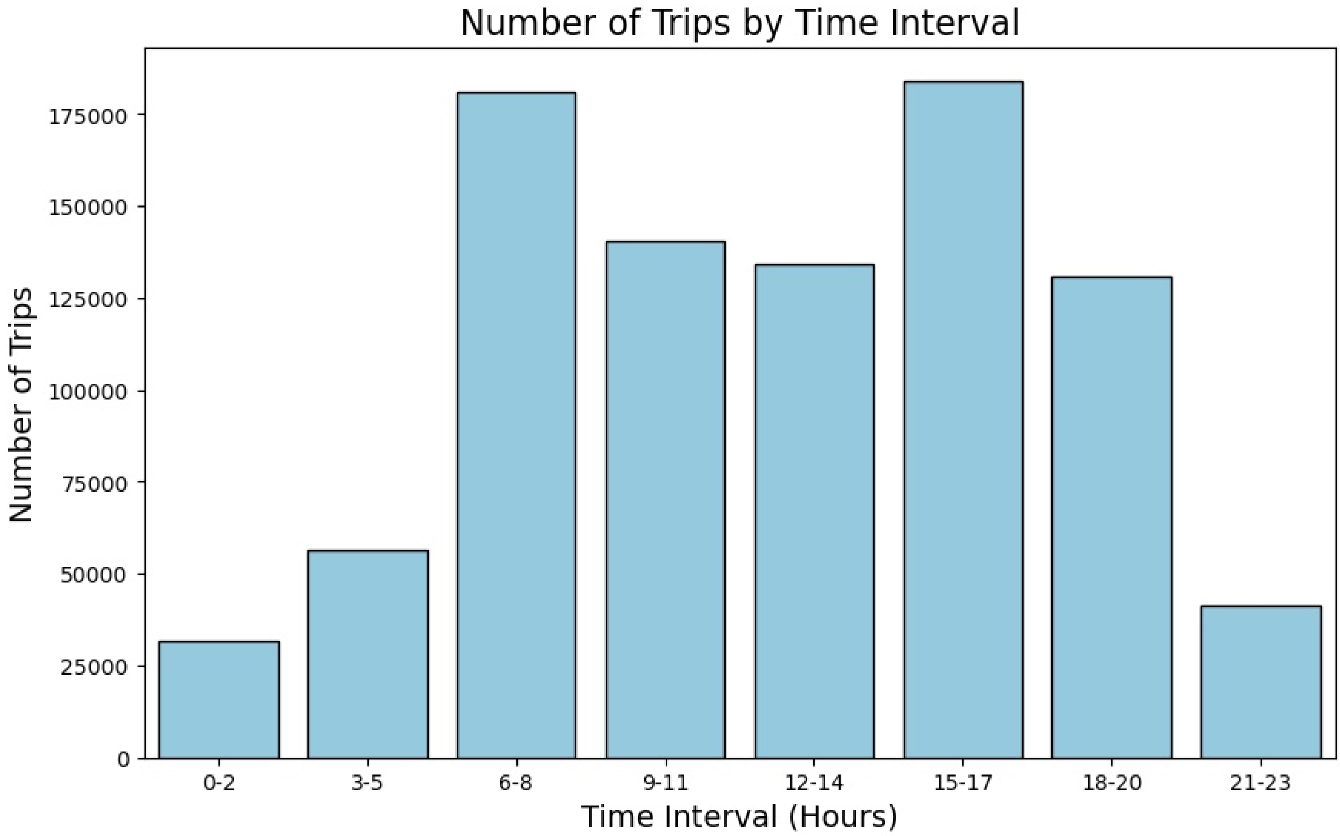
```
q1_ds = final_ds.copy()
q1_ds['Start Range Hour'] = q1_ds['Start Time'].apply(get_range_hour)
q1_ds['Index Range Hour'] = q1_ds['Start Time'].apply(get_range_hour_idx)
q1_ds = q1_ds[['Index Range Hour','Trip.id','Start Range Hour']].copy()
q1_ds.dropna(inplace=True)
q1_ds_group = q1_ds.groupby(['Index Range Hour','Start Range Hour']).count().sort_values(by='Index Range Hour')
q1_ds_group
```

Out[14]:

Index Range Hour	Start Range Hour	Trip.id
0	**0-2**	31861
3	**3-5**	56443
6	**6-8**	180982
9	**9-11**	140415
12	**12-14**	133977
15	**15-17**	184066
18	**18-20**	131028
21	**21-23**	41228

In [15]:

```
plt.figure(figsize=(10, 6))
sns.barplot(x='Start Range Hour', y='Trip.id', data=q1_ds_group, color='skyblue', edgecolor='black')
plt.title("Number of Trips by Time Interval", fontsize=16)
plt.xlabel("Time Interval (Hours)", fontsize=14)
plt.ylabel("Number of Trips", fontsize=14)
sns.set_theme(style="whitegrid")
plt.show()
```



The two time slots with peaks on weekdays are:

- 6 AM to 9 AM: 180,982 trips.
- 3 PM to 6 PM: 184,066 trips. The "M" shape of this graph is common in the automotive field as these time slots indicate travel related to work commitments.

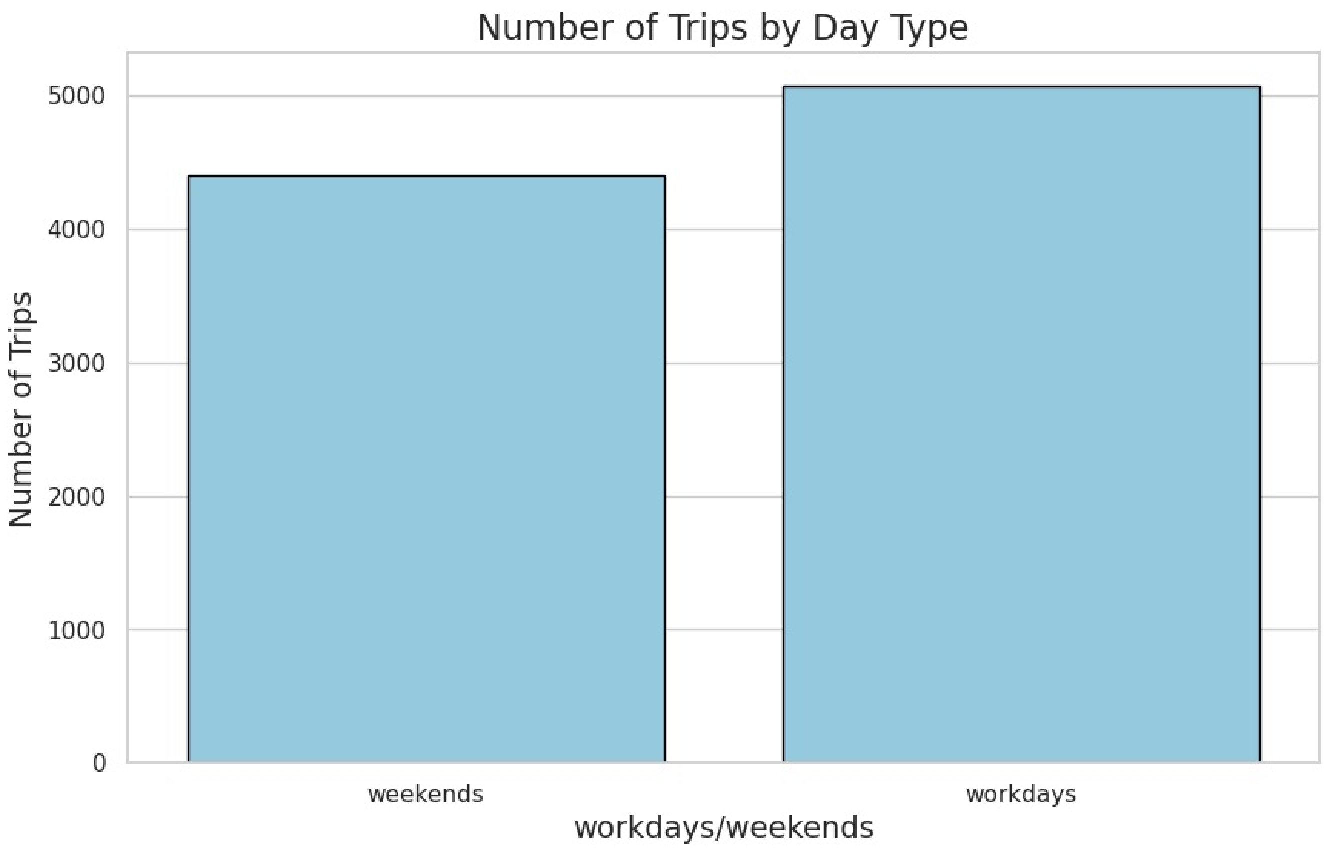
Question 2 Does the volume of trips vary on average between orkkdays and weekends?

In [16]:
```
q2_ds = final_ds.copy()
q2_ds = q2_ds[['Trip.id','Start Time']].dropna()
q2_ds['Start Date'] = q2_ds['Start Time'].dt.date
q2_ds['Day Type'] = q2_ds['Start Time'].dt.weekday.apply(lambda x:'weekends' if x > 5 else 'workdays')
q2_ds_group = q2_ds[['Start Date','Day Type','Trip.id']].groupby(['Start Date','Day Type']).count().groupby(['Da
q2_ds_group = q2_ds_group
q2_ds_group
```

Out[16]:

	Trip.id
Day Type	
weekends	4403.923077
workdays	5067.729032

In [17]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x='Day Type', y='Trip.id', data=q2_ds_group, color='skyblue', edgecolor='black')
plt.title("Number of Trips by Day Type", fontsize=16)
plt.xlabel("workdays/weekends", fontsize=14)
plt.ylabel("Number of Trips", fontsize=14)
sns.set_theme(style="whitegrid")
plt.show()
```



As evidenced by the graph, the average volume of trips per day varies between workdays and weekends. On weekends, people tend to take fewer trips compared to workdays.

Question 3

Based on the available data, where is the driver target concentrated in terms of age group and gender?

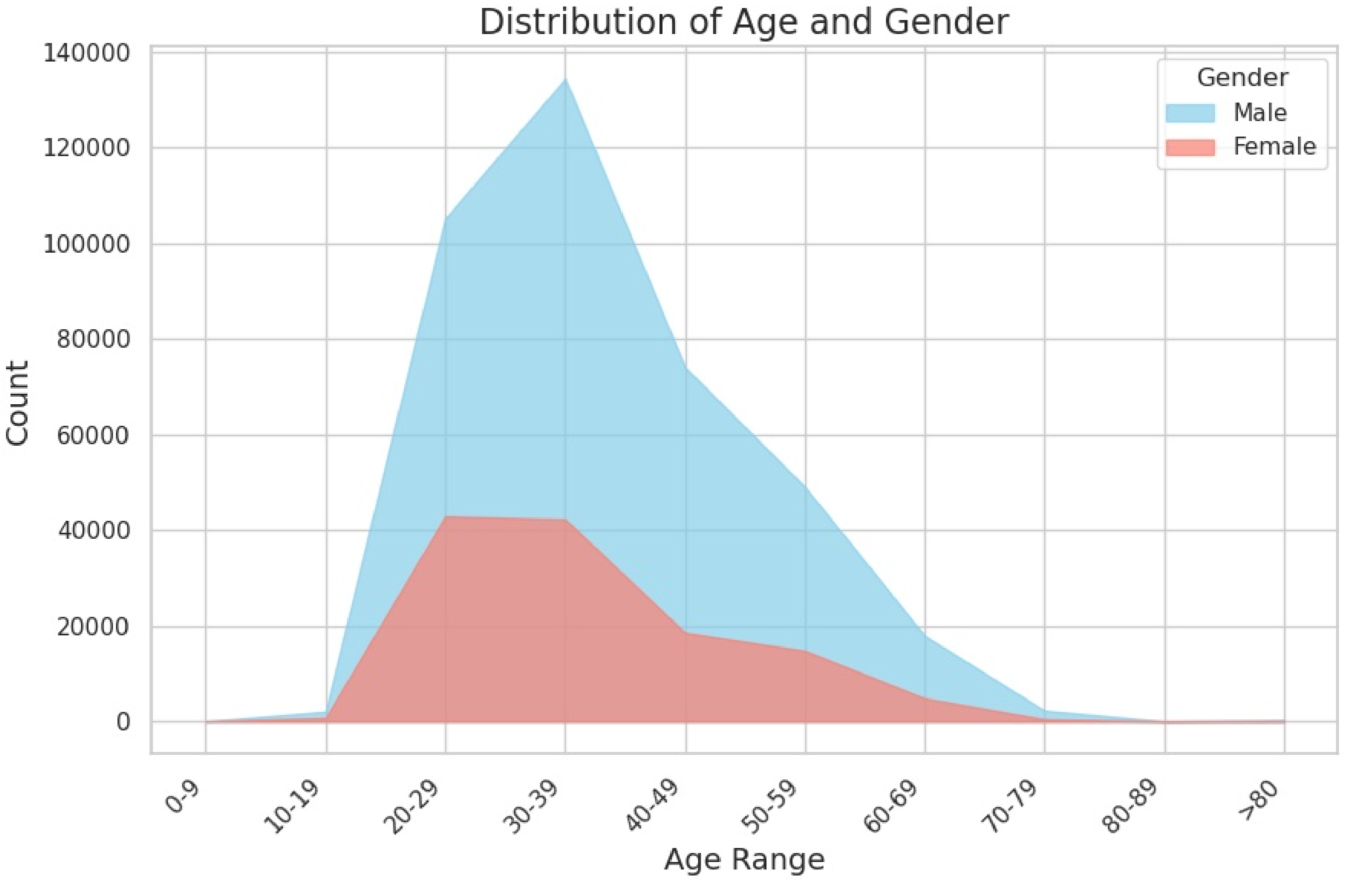
In [18]:
```
q3_ds = final_ds.copy()
q3_ds = q3_ds[['Gender','Birth Year','Start Time']]
q3_ds.dropna(inplace=True)
q3_ds['Birth Year'] = q3_ds['Birth Year'].astype(int)
q3_ds['Age'] = q3_ds['Start Time'].dt.year - q3_ds['Birth Year']
q3_ds['Age Range'] = q3_ds['Age'].apply(get_range_age)
q3_ds.drop(columns=['Birth Year','Start Time'],inplace=True)
q3_ds_group = q3_ds.groupby(['Age Range','Gender']).count()
q3_ds_group = q3_ds_group.reset_index()
q3_ds_pivot = q3_ds_group.pivot(index='Age Range', columns='Gender', values='Age').fillna(0)
q3_ds_pivot
```

Out[18]:

Gender	Female	Male
Age Range		
0-9	0.0	6.0
10-19	737.0	2043.0
20-29	42892.0	105198.0
30-39	42257.0	134398.0
40-49	18540.0	74057.0
50-59	14782.0	49049.0
60-69	4833.0	17898.0
70-79	438.0	2258.0
80-89	6.0	8.0
>80	51.0	279.0

In [19]:
```
plt.figure(figsize=(10, 6))
plt.fill_between(q3_ds_pivot.index, q3_ds_pivot['Male'], alpha=0.7, label='Male', color='skyblue')
plt.fill_between(q3_ds_pivot.index, q3_ds_pivot['Female'], alpha=0.7, label='Female', color='salmon')
plt.title("Distribution of Age and Gender", fontsize=16)
plt.xlabel("Age Range", fontsize=14)
plt.ylabel("Count", fontsize=14)
```

```
sns.set_theme(style="whitegrid")
plt.xticks(rotation=45, ha='right')
plt.legend(title='Gender')
plt.show()
```



The graphs show that the primary target of our users is males aged between 30 and 39 years.

Finishing Up

> Congratulations! You have reached the end of the Explore Bikeshare Data Project. You should be very proud of all you have accomplished!

> **Tip**: Once you are satisfied with your work here, check over your report to make sure that it is satisfies all the areas of the rubric.

Directions to Submit

> Before you submit your project, you need to create a .html or .pdf version of this notebook in the workspace here. To do that, run the code cell below. If it worked correctly, you should get a return code of 0, and you should see the generated .html file in the workspace directory (click on the orange Jupyter icon in the upper left).

> Alternatively, you can download this report as .html via the **File** > **Download as** submenu, and then manually upload it into the workspace directory by clicking on the orange Jupyter icon in the upper left, then using the Upload button.

> Once you've done this, you can submit your project by clicking on the "Submit Project" button in the lower right here. This will create and submit a zip file with this .ipynb doc and the .html or .pdf version you created. Congratulations!

In [ ]:
```
jupyter nbconvert --to html Explore_bikeshare_data.ipynb
```

In [ ]:
```
wkhtmltopdf Explore_bikeshare_data.html Explore_bikeshare_data.pdf
```